THEME ARTICLE: CONNECTED LIVING

Enhancing Winter Road Maintenance via Cloud Computing

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In this article, we develop an AI-enhanced cloud computing framework to enable the autonomous decision-making quality and precision of winter road operations for connected living, namely, the Smart Maintenance Decision Support System (SmartMDSS). With support from the Federal Highway Administration and Michigan Department of Transportation, we are among the first to develop AI-enabled tools for practical winter road maintenance decision making. On the front end, SmartMDSS provides a user-friendly graphical interface showing all of the valuable data and winter operations for specific points on the road and sends necessary warnings and notifications. On the back end, SmartMDSS extracts and analyzes data and makes winter road maintenance decisions. A convolutional neural network has been successfully employed to identify the snow coverage on the road surface. Decision-making algorithms were proposed and implemented to support the road engineers and operators for real-time winter maintenance operations.

The United States has more than 4 million miles of roads that are essential for the economy and daily life.[1] Highways account for 6% of public spending, with $165 billion spent on them in 2014; 45% of this spending went toward winter road maintenance, which is a top priority for more than 30 states. Winter weather damage costs more than $2.5 billion in state and local agencies' expenditures[2] and $11.7 billion in corrosion damage to vehicles, and it poses safety and mobility issues for people.[3]

New technologies and AI have improved the connection between humans and their environments. State departments of transportation (DOTs) have invested billions into data acquisition systems for highway infrastructure, providing more accurate and autonomous road maintenance tools. This allows for a more connected approach to winter road maintenance, with opportunities to enhance it through the use of new data.

Winter road maintenance aims to improve comfort, safety, and economic benefits for road users. A decision support system helps decide which maintenance operations to apply based on available data and resources. As cities and paved roads grew, researchers provided operators with instructions and decision support systems. The decision-making process requires data as the input, and real-time insights and predictions are the output to optimize the performance of road agencies. The amount and quality of data directly influence the accuracy of the decisions made.

On-road surveillance cameras have been used for monitoring road network systems to manage traffic by observing incidents, traffic conditions, and visibility distance. This tool provides assistance to transportation managers to improve traffic flow. Previous attempts to automate road surface condition detection using traditional image processing techniques have been made for winter maintenance.[4] However, new AI-based image processing methods have not been explored for this purpose.

AI and machine learning (ML) tools enable engineers to evaluate large amounts of data, providing advantages for improving cold region road maintenance systems. By continuously processing image data, these technologies can help operators make faster and more accurate decisions. Some studies applied ML classification on images from surveillance cameras for different purposes, such as object recognition, vehicle type classification,[5] surface defect recognition,[6] human pose detection,[7] traffic management, and plate

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recognition.[8] The convolutional neural network (CNN) revolutionized image classification models by automatically extracting features from raw pixel data, making it an efficient tool to estimate the likelihood of an image belonging to a specific class.

In this article, we develop a cloud computing platform, the Smart Maintenance Decision Support System (SmartMDSS), which improves road condition assessment with deep learning, autonomous decision making, and automatic data acquisition, processing, and computing. With support from the Federal Highway Administration (FHWA) and Michigan DOT (MDOT), we are among the first to develop an AI-enabled tool for practical winter road maintenance decision making. The advantages of SmartMDSS have been demonstrated in this pilot study: 1) the tool becomes more intelligent as more data are received, 2) SmartMDSS can significantly reduce administrators' need to install instrumentation devices on the roads, and 3) the tool can be easily adjusted for local road agencies for instant budget savings in road maintenance.

SMARTMDSS FRAMEWORK

This FHWA project aims to create a web-based app with AI-enhanced cloud computing to improve winter maintenance systems. SmartMDSS provides a graphical interface and real-time data analysis for autonomous decision making. A decision-making algorithm was developed using weather and traffic data as well as a CNN for accurate road condition sensing. The tool is easily modifiable for use in other locations globally and is available at www.smartmdss.org.

Features and Benefits

The SmartMDSS framework, as shown in Figure 1, could lead to immeasurable savings in the financial plan of state DOTs, local road agencies, and drivers. In the current version, compared to the other maintenance decision support systems, the web-based tool we are developing has a series of features and benefits:

- First, road images are a valuable and accessible qualitative data set that can be used in addition to traffic, road, and weather data without the need for specialized equipment or training.
- Second, the CNN algorithm determines the state of the road's surface by estimating the snow coverage from raw images. The model is trained to constantly update with new images, improving the prediction accuracy over time intervals.
- Third, SmartMDSS utilizes multiple application programming interfaces (APIs) to support and verify weather, road surface, and traffic data. The app is designed to continue functioning even if the camera connection is broken or visuals are unclear, and it can forecast impending disasters such as snowstorms.
- Next, the SmartMDSS interface includes a map with bubbles representing surveillance camera locations and the road condition. Clicking on the bubble displays information on the road traffic, weather forecast, road image, state, and proposed maintenance actions.
- Finally, the SmartMDSS app uses data analysis to predict road maintenance actions based on regulations gathered from road maintenance agency instructions.

Back End

The SmartMDSS back-end package is composed of five major parts, as shown in Figure 1. The database includes these parts and is updated with traffic data (from a road information API), weather information (from a weather API), road surface temperature information [from the Road Weather Information System (RWIS) API], and road conditions (by taking road images and CNN analysis models). The minor back-end sections are as follows:

- *Road image scraping from the surveillance camera website*: The SmartMDSS app uses real-time images from more than 700 locations along U.S. roadways to determine road surface conditions using a CNN model. A Python module called "Selenium" is used to automatically gather data from the MDOT website, including road names, coordinates, and images, which are imported into a NoSQL database for use in the app.
- *Traffic data*: The "Tomtom API" provides real-time traffic data on speed, incidents, and closures, and it updates every minute. These data are captured and inserted into the MongoDB database used by the SmartMDSS app.
- *Weather data*: The "Open Weather Map API" provides weather data for temperature, humidity, wind speed, visibility, and weather forecasts for the upcoming hours and days. These data are important for winter road management decision making.
- *Road surface temperature data*: SmartMDSS utilizes the RWIS API to gather information on the road surface temperature. There are approximately 90 active RWIS stations in Michigan state that measure real-time road surface data, including

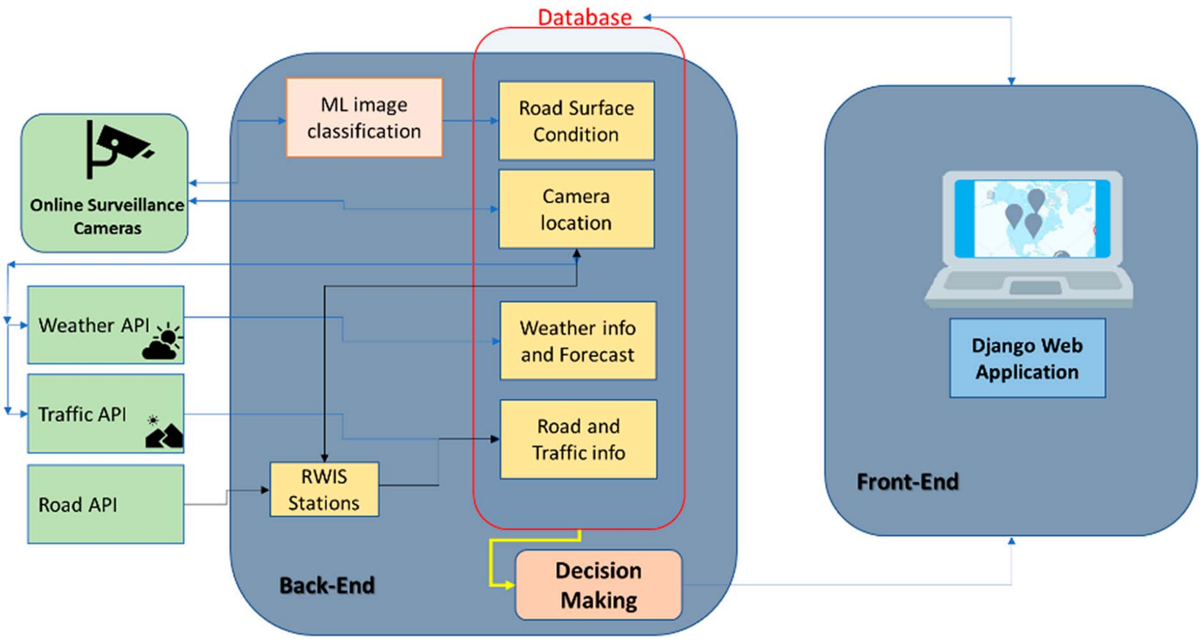


FIGURE 1. Overview of the Smart Maintenance Decision Support System (SmartMDSS) framework. API: application programming interface; ML: machine learning; RWIS: Road Weather Information System.

temperature, and the app assigns the temperature from the nearest station to each point on the map.

- *Decision-making data*: SmartMDSS monitors real-time data to suggest winter maintenance operations based on weather, road, and traffic data using the decision support system. The visual presentation of the data is shown on the front end of the app. Before that, some important events should be bold as a heads-up or alert. The alert representations on the web-based app are described in the "Front End" section. In the current version of SmartMDSS, the color blue indicates normal road and weather conditions. The yellow sign is used when a heavy snowstorm is on the way or there is a chance of ice formation, and the color red is used as the surface road condition turns snowy, the current weather shows heavy snow, or the traffic flow is blocked for any reason. By exploring the app's map, the user can realize the road's general status by looking at the bubble color above each point.
- *Database*: A database will access a large volume of data so that multiple users can read, modify, search, and sort data fast and easily. All of the data gathered from the 1) road point name and location, 2) road surface condition recognition by CNN, 3) weather data, and 4) traffic data are gathered in the database. In this app, the "MongoDB" database was used. This program is classified as a NoSQL database that uses JavaScript Object Notation-like documents with optional schemas. Finally, all of the data required for the app are now cumulated into the database. In the next section, the app representation is discussed.

Front End

SmartMDSS is an app that uses road surveillance cameras as a new source of data to fully understand the condition of roads during winter. The app will scrape information from weather and road data sources, evaluate road image data using the CNN model, and import all of the information into the database. Based on the gathered data, SmartMDSS will suggest winter operations established by a decision-making algorithm and display the information on a map. The web interface was constructed using Django, and the map interface was created using Leaflet. Django connects to the MongoDB database and imports the most recent data, while Leaflet produces a geo pin for each point and attaches relevant data to the pin. Figure 2 displays the map and the pop-up data format.

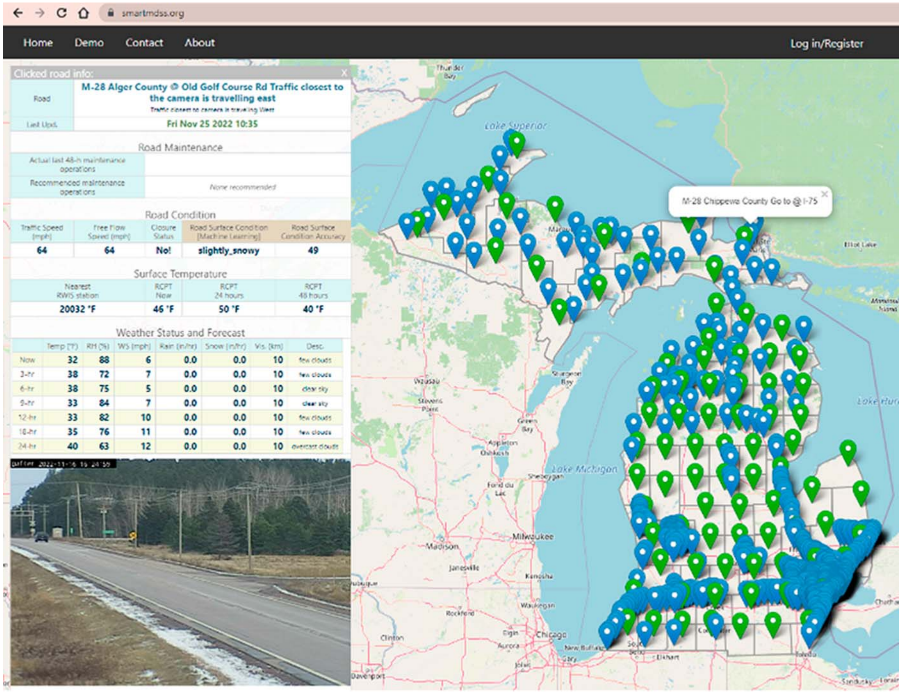


FIGURE 2. Web interface of SmartMDSS for Michigan and data visualization for a specific point.

ROAD SURFACE MONITORING

In this research, a CNN algorithm was used to monitor the road surface condition. This research uses a CNN algorithm to monitor road surface conditions. CNNs are a subgroup of deep neural networks that perform well in applications related to image data. They have multiple layers, including convolutional, nonlinearity, pooling, and fully connected layers. CNNs detect features in images similar to how our brains recognize objects—by analyzing different aspects of the image and combining them to identify the object.

A CNN uses filters to detect features in an image, similar to how our brains work. Each filter is a window that scans the image and identifies a specific feature. In the case of a snowy road, the CNN uses line, color, and pattern filters to detect road borders and snow

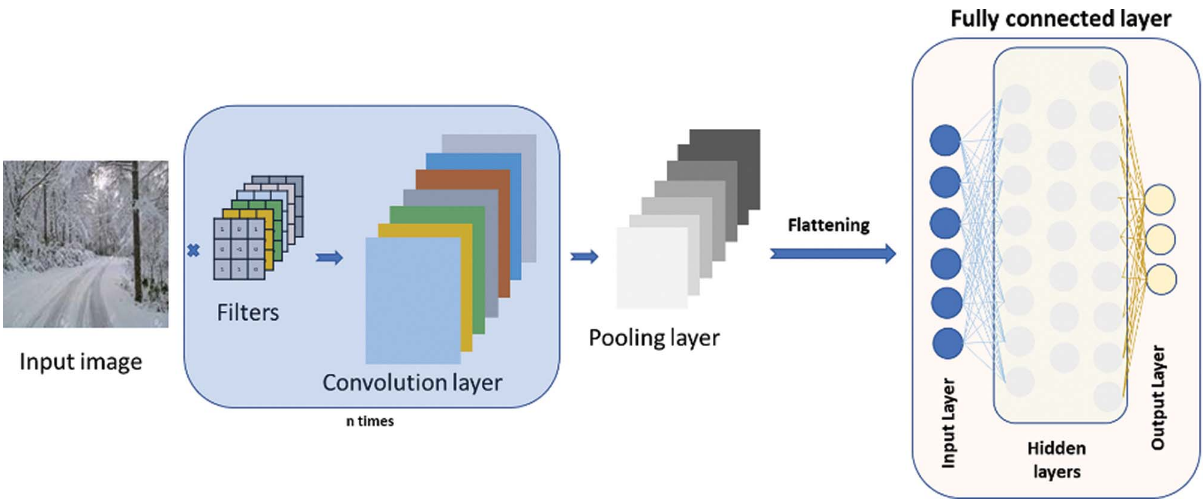
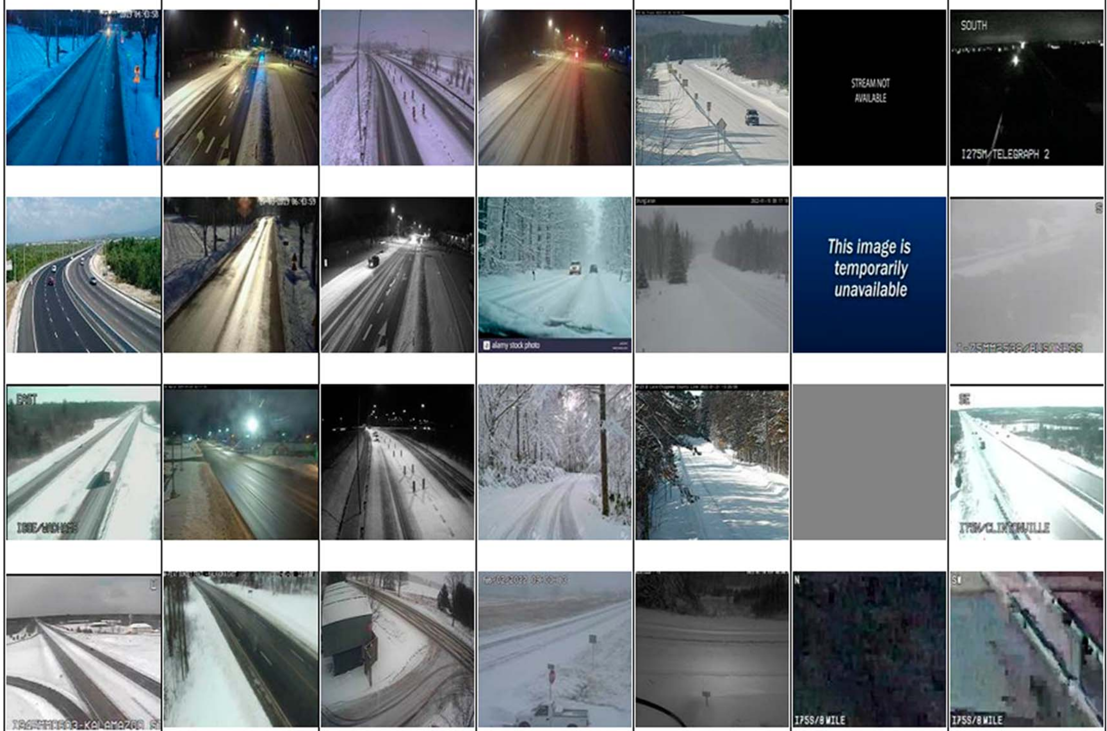


FIGURE 3. Convolutional neural network structure.

TABLE 1. Road surface image classification for the convolutional neural network training.

Class	Dry Surface	Wet surface	Slightly Snowy	Med Snowy	Heavy snowy	No image	Not Clear
Number of Images	457	470	521	418	360	72	135
Image samples							



coverage. The CNN then recognizes the snowy road by detecting overlapping objects. The image is processed through convolution and pooling layers to decrease its size and extract features. The pooling layer reduces the dimension of the convolutional layer by obtaining the average or maximum value of nearby cells. Figure 3 depicts a CNN's structure. The pooling layer has three benefits: it reduces dimensions and computation effort, reduces overfitting, and allows for position-invariant feature detection. Flattening the final output and using a regular artificial neural network for classification is the next step.[9] To train a CNN model, a large number of images are needed, and the fully connected layer's shape, the dataset's size, and the number of iterations all affect the accuracy of the model's predictions. This study shows that using a CNN to classify road conditions is feasible and beneficial because it can recognize features faster and more deeply than the human eye, even when distinguishing between subtle differences like a wet or slightly icy road surface.

The dataset for generating the CNN model consists of 2433 images gathered mostly from the MDOT website during winter 2022 and more images added from Grabowski's database.[10] We categorized the images into seven classes. There are five classes describing the road's surface: dry, wet, slightly snowy, relatively medium snowy, and heavily snowy. Additionally, there are two groups for cases with no images or unclear visuals, as shown in Table 1. According to our criteria for developing the database for the snow coverage intensity, when less than 30% of the road is covered in snow, it is referred to as slightly snowy. This is akin to displaying some snowy strips on the road. The term "medium snowy" denotes a snow coverage between 30% and 70%. At this point, there are still some visible strips of the road surface on the tire tracks. Heavy snowfall is defined as more than 70% snow coverage, at which point the tire tracks begin disappearing. Overall, 90% of the database was used to train the CNN model, and the remaining 10% was used for the validation.

In the case in which the dataset is not adequately rich or when there is an overfitting problem with the CNN model, the data augmentation technique will help to amend these issues. Data augmentation is a technique for producing new training data from

TABLE 2. Decision-making process chart.

Pavement Temperature	Weather Condition	Anti-icing (Before storm)	plowing (During & after storm)	Deicing (During and after storm)	Comment
Above 32°F or rising	Light snow	None or T1	plow as needed	None	Comment 1
	Moderate Snow	None or T1	plow as needed	None	Comment 1
	Heavy Snow	None or T1	plow as needed	None	Comment 1
	Freezing rainstorm	None or T2	None	None	Commnet 1
	Sleet storm	None or T1	None	None	Commetn 1
32°F - 30°F	Light snow	T3	plow as needed	T3	Comment 2
	Moderate Snow	T4	plow as needed	T5	Comment 3
	Heavy Snow	T4	plow as needed	T5	Comment 4
	Freezing rainstorm	T6	plow as needed	T6	Comment 5
	Sleet storm	T7	plow as needed	T7	Comment 6
25°F - 30°F	Light snow	T8	plow as needed	T3	Comment 2
	Moderate Snow	T8	plow as needed	T5	Comment 3
	Heavy Snow	T9	plow as needed	T10	Comment 3
	Freezing rainstorm	T11	plow as needed	T11	Comment 7
	Sleet storm	T12	plow as needed	T12	Comment 6
20°F - 25°F	Light snow	T13	plow as needed	T13	Comment 2
	Moderate Snow	T14	plow as needed	T15	Comment 8
	Heavy Snow	T14	plow as needed	T15	Comment 9
	Freezing rainstorm	T11	Plow as needed	T11	Comment 7
	Sleet storm	T16	Plow as needed	T16	Comment 10
15°F - 20°F	Light snow	T17	plow as needed	T17	Comment 11
	Moderate Snow	T17	plow as needed	T18	Comment 6
	Heavy Snow	T14	plow as needed	T15	Comment 9
	Freezing rainstorm	T16	plow as needed	T16	Commnet 12
	Sleet storm	T16	plow as needed	T16	Commetn 11
Below 15°F	Light snow	T19	plow as needed	T19	Comment 13
	Moderate Snow	T19	plow as needed	T19	Comment 13
	Heavy Snow	T19	plow as needed	T19	Comment 13
	Freezing rainstorm	T19	plow as needed	T19	Comment 13
	Sleet storm	T19	plow as needed	T19	Comment 13

Notes:
Consider applying anti-icing material during low-traffic periods. [11pm-4am and 2pm-4pm].
When frost on the shoulder begins moving into the traveled lanes, reapply chemicals.
Consider spot applications on hills, curves, and intersections.
Apply liquids at half the rate (not half the concentration) for the first application of the season, or after a prolonged dry spell. On dry roads, liquids tend to mix with the oil from vehicles and cause slippery conditions if over-applied.
Avoid anti-icing under blowing conditions, in areas prone to drifting, or anywhere else you would not use salt.
Avoid applying before a predicted heavy rain.
A salt/sand mix is generally not recommended as salt reduces the effectiveness of sand, and sand reduces the effectiveness of salt.

Treatment	Dry salt (lbs/lane-mi)			Abrasives (lbs/lane-mile)
	Liquid	prewetted	Dry salt	
T1	Up to 40	Up to 35	50 to 100	
T2	Up to 40	75 to 100	50 to 100	
T3	100	80 to 100	50 to 100	
T4	100	100	90 to 120	
T5	Subsequent light snow: 100 Subsequent heavy snow: 200	Subsequent light snow: 100 Subsequent heavy snow: 200	Subsequent light snow: 100 Subsequent heavy snow: 200	
T6	75 to 100	75 to 100	90 to 100	
T7	125	125	125	
T8	100	60 to 80	75 to 100	
T9	200	150 to 200	150 to 200	
T10	200	200	200	
T11		Recommended 75 to 250	75 to 250	
T12		Recommended 125 to 325	200 to 300	
T13	100	80 to 120	100 to 150	
T14		Recommended 80 to 200	120 to 300	If 15°F - 20°F: 400
T15		Recommended 100 to 250	120 to 300	If 15°F - 20°F: 400
T16		Recommended 250 to 400	250 to 400	If 15°F - 20°F: 400
T17		Recommended 120 to 200	150 to 200	If 15°F - 20°F: 400
T18		Subsequent light snow: T17 Subsequent heavy snow: T16		If 15°F - 20°F: 400
T19		Other chemicals blended with abrasives		500-750

	Comments
Comment 1	1- Monitor Pavement temp 2- Treat chemicals if needed 3- Treat intersections and curves
Comment 2	1- Do not apply the liquid onto packed snow 2- Applications will need to be more frequent at lower temperatures and higher snowfall rates. 3- It is not advisable to apply a liquid chemical at the indicated spread rate when the pavement temperature drops below -5°C (23°F)
Comment 3	1- Applications will need to be more frequent at lower temperatures and higher snowfall rates, heavy snow accumulation or packed snow 3- After heavier snow periods and during a light snowfall, reduce the chemical rate to 28 kg/lane-km (100 lb/lane-mi); continue to plow and apply chemicals as needed
Comment 4	1- If the desired plowing/treatment frequency cannot be maintained, the spread rate can be increased to 55 kg/lane-km (200 lb/lane-mi) to accommodate longer operational cycles 2- Do not apply liquid chemicals onto heavy snow accumulation or packed snow
Comment 5	Monitor pavement temperature and precipitation closely
Comment 6	1- Monitor pavement temperature and precipitation closely 2- Increase spread rate toward a *higher indicated rate* with an increase in sleet intensity 3- Decrease spread rate toward *lower indicated rate* with a decrease in sleet intensity
Comment 7	1- Monitor pavement temperature and precipitation closely 2- Increase spread rate toward a *higher indicated rate* with a decrease in pavement temperature or increase in the intensity of freezing rainfall 3- Decrease spread rate toward *lower indicated rate* with increase in pavement temperature or decrease in intensity of freezing rainfall
Comment 8	1- If sufficient moisture is present, a solid chemical without prewetting can be applied 2- Reduce chemical rate to 55 kg/lane-km (200 lb/lane-mi) after heavier snow periods and during light snowfall; continue to plow and apply chemicals as needed
Comment 9	1- If the desired plowing/treatment frequency cannot be maintained, the spread rate can be increased to 140 kg/lane-km (500 lb/lane-mi) to accommodate longer operational cycles 2- If sufficient moisture is present, a solid chemical without prewetting can be applied
Comment 10	1) Monitor precipitation closely 2) Increase spread rate toward a *higher indicated rate* with a decrease in pavement temperature or increase in sleet intensity 3) Decrease spread rate toward a *lower indicated rate* with an increase in pavement temperature or decrease in sleet intensity
Comment 11	1- If sufficient moisture is present, a solid chemical without prewetting can be applied 2- Plow as needed; reapply prewetted solid chemical when needed
Comment 12	1- Monitor precipitation closely 2- Increase spread rate toward a *higher indicated rate* with an increase in the intensity of freezing rainfall 3- Decrease spread rate toward *lower indicated rate* with a decrease in intensity of freezing rainfall
Comment 13	1- It is not recommended that chemicals be applied in this temperature range 2- Apply abrasives a needed

existing examples by applying random modifications, such as rotating, flipping, zooming, etc., resulting in believable-looking visuals. This allows the model to be exposed to more parts of the data and generalize more effectively. In this research, we used four types of data augmentation: random flipping, random zooming, random rotation, and random rescaling.

The CNN model used three convolution blocks with a max pool layer in each of them and a rectified linear unit activation function. To determine the optimum epoch number, the model was trained up to 300 epochs, and the loss values were plotted against the number of epochs. The optimal number for the epoch was 200, as, beyond this point, the model showed overfitting on the training data. At epoch 200, the training set loss becomes nearly zero.

The training and validation accuracy for the trained CNN model with data augmentation are 99.74% and 94.76%, respectively. Without data augmentation, the accuracy dropped by 2%. Data augmentation also decreased the training and validation loss by about 0.2, showing that the data augmentation technique can improve feature detection. The results confirm that the CNN was well trained for road surface detection.

DECISION MAKING

The primary objective of the SmartMDSS app is to offer real-time suggestions for winter maintenance operations. A thorough policy algorithm that can consider practically all weather, road, and traffic scenarios and provide a solution for all situations is necessary for the decision support system. To make proper autonomous decisions with the SmartMDSS app, we gathered several winter maintenance instructions, including *Local Roads Maintenance Workers' Manual*,[11] "A New Paradigm for Winter Maintenance Decisions,"[12] *Manual of Practice for an Effective Anti-icing Program*,[13] and *Michigan Winter Maintenance Manual*.[14] We have investigated several websites from winter road maintenance firms and interviewed some road operators. The summary of this evaluation is provided in Table 2, which displays the decision-making chart.

Table 2 concentrates more on the salting operations, including anti-icing, de-icing, and abrasives. For plowing operations, we need real-time data describing the road surface status. Here, the CNN helps detect the road surface condition and make decisions for snowplowing operations. The app would not advise plowing in situations when the road surface is "wet" or has a "slightly snowy" coverage because it might harm the road surface. Plowing is recommended for medium and heavy snowy roads. Using Table 2 and the CNN model for road surface detection, the SmartMDSS app is equipped with a decision-making model for winter road maintenance operations. The next section discusses other features and parts of SmartMDSS. Since the app is dealing with a large number of constantly updating data and operations for hundreds of different locations on roads, user-friendly visualization and an organized database are required.

RESULTS

The main purpose of this research was to develop a winter road maintenance decision-making app with an AI-enhanced framework in which data can be analyzed in real time for autonomous decision making. The CNN model provides the current state of the road surface. Additional information is obtained from several API sources, including traffic, road conditions, and weather data. A database is used to store the gathered data. The app offers a recommended winter operation for the following 24 h after assessing the data for each particular spot on the road and using a decision-making algorithm.

The SmartMDSS program continually monitors the weather forecast during the decision-making process. As soon as the app detects an upcoming snowfall in the following days, it determines the quantity of salting and the ideal timing at which to apply the chemicals and abrasives to the road depending on the surface

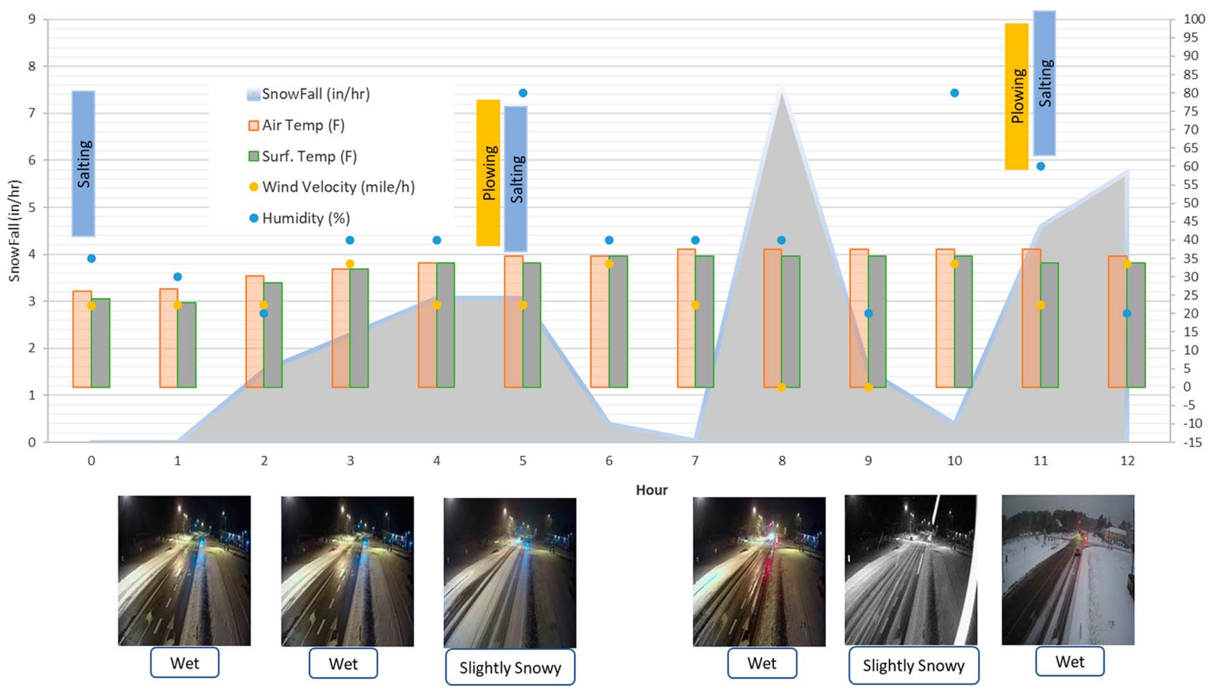


FIGURE 4. Example of the decision-making process during a 12-h snowstorm. Surf.: surface.

temperature and snowfall intensity (anti-icing operation). To reduce interference of the salting operations with traffic flow, the program also suggests the optimal time for salting operations based on the lowest traffic flow. The app checks the images from the surveillance cameras during the storm to assess the state of the road surfaces. In any event, the app will also keep track of traffic information and surface temperatures if it cannot obtain a clear vision of the road.

During the snowstorm, the app alerts the operators to prepare for plowing and calculates the next salting operation specifics as soon as the road surface state changes to “slightly snowy” (de-icing operation). In the absence of a road image, the app alerts operators to keep an eye on the road’s surface if traffic slows. The app continuously monitors the traffic condition to alert the traffic operators of any changes.

Figure 4 shows a snowfall event simulation to better understand how the SmartMDSS app makes decisions. The program recommends an anti-icing operation (100 lb/lane-mi) at hour “0,” as soon as the forecasting data indicate snowfall will start in an hour. The salt on the road dissipated after 5 h of heavy snowfall, and a thin layer of snow covers the road surface. Therefore, the app requires a plowing operation and another salting (de-icing) operation (50 lb/lane-mi). The salt will last for another 6 h, and the app decides to act for the second plowing and the third salting operation. The app will continuously watch the weather/road/traffic data for more winter operations.

To ensure that the decision-making algorithm is providing the most accurate response, the app continuously updates the algorithm under the supervision of road engineers and operators. It should be noted that, depending on the local climate, snowfall, and road surface characteristics, the best decision-making algorithm may alter for different areas. Additionally, suggested winter maintenance activities might exceed the road agencies’ supplies and machinery. The SmartMDSS app is designed such that localized upgrades to the decision-making algorithm are possible. However, we need feedback from local road engineers and operators to develop localized decision-making algorithms. The next version of the SmartMDSS app will have a two-way connection with operators to assess their equipment and upgrade the localized decision-making algorithm based on their feedback.

CONCLUSION

In this article, an AI-enhanced cloud computing framework was developed, which enables autonomous decision-making quality and precision for winter road operations. This framework and web-based app have started to be used by practitioners for winter road maintenance. More functions will be enabled in our future work toward more intelligent connected living.

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